

Megapixel Topology Optimization using *fW*-mean Filters

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Material distribution (topology optimization)

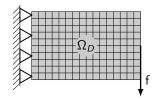
- \blacktriangleright Distribute material arbitrarily in the design domain Ω_D
- \blacktriangleright Material distribution function ρ ("density") constant in each element

Example

Linear elasticity, minimization of compliance

- $\rho_i = 0$ if void and 1 if solid
- Want to solve:

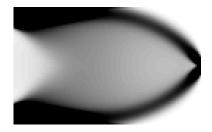
$$\begin{array}{l} \min_{\boldsymbol{\rho}} \quad J(\boldsymbol{\rho}) \quad (\text{compliance}) \\ \text{s.t.} \quad \rho_i \in \{0,1\} \quad \forall i \\ \quad \frac{1}{n} \sum_{i=1}^n \rho_i \leq V \\ \quad \text{governing PDE} \end{array}$$





Large-scale non-linear integer optimization problems are very hard to solve. . .

- Relaxation: $0 \le \rho_i \le 1$
- Penalization: force ρ_i to either 0 or 1
 - Mesh dependence
- Filtering
 - Minimum length scale
 - Intermediate densities
 - Computationally expensive





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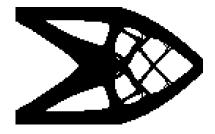
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Quasi-arithmetic means (f-means)

- Weighted arithmetic mean $M_x(\mathbf{x}; \mathbf{w}) = \mathbf{w}^T \mathbf{x} \equiv \sum_{i=1}^n w_i x_i$ $\mathbf{w}^T \mathbf{1}_{\mathbf{n}} \equiv \sum_{i=1}^n w_i = 1$ $w_i > 0$
- Weighted harmonic mean $M_{x^{-1}}(\boldsymbol{x}; \boldsymbol{w}) = (\boldsymbol{w}^T \boldsymbol{x}^{-1})^{-1}$

▶ ...



• Weighted geometric mean $M_{\ln x}(\mathbf{x}; \mathbf{w}) = \prod_{i=1}^{n} x_i^{w_i} \equiv \exp(\mathbf{w}^T \ln \mathbf{x})$

Quasi-arithmetic mean (f-mean)

$$M_f(\mathbf{x}; \mathbf{w}) = f^{-1}(\mathbf{w}^T \mathbf{f}(\mathbf{x})) \iff f(M_f) = \mathbf{w}^T \mathbf{f}(\mathbf{x})$$



fW-mean filters (Wadbro and Hägg, 2015)

Replace the value of the design variable in one element with the f-mean of the values of its neighboring elements:

fW-mean filter

- ► $F(\rho) = f^{-1}(Wf(\rho))$ $W = [w_{ij}] \in \mathbb{R}^{n \times n}$ $w_{ij} \ge 0$ and $W1_n = 1_n$
- $w_{ij} > 0$ iff $j \in \mathcal{N}_i \subset \{1, \ldots, n\}$
- Replace f^{-1} with g, then a vast majority of available filters
 - Heaviside filter (Guest et al., 2004),
 - Morphology-based filters (Sigmund 2007),
 - Pythagorean mean based filters (Svanberg and Svärd, 2014)

can be handled in a similar manner

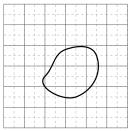


Computational complexity of fW-mean filtering

- d-dimensional Cartesian grid with n elements of size h
- Neighborhoods with fixed physical size $V \propto (hr)^d$
 - r is the filter radius (measured in number of elements)
- Computational complexity: $O(n|\mathcal{N}_i|)$

$$\begin{cases} |\mathcal{N}_i| \propto h^{-d} (hr)^d \\ r^d \propto n \end{cases} \Rightarrow O(n|\mathcal{N}_i|) = O(n^2) \end{cases}$$

To achieve O(n), additional assumptions on \boldsymbol{W} and the geometry of the neighborhoods are needed





Equal weight fW-mean filters

$$W = D^{-1}G$$

$$D = \operatorname{diag}(|\mathcal{N}_1|, \dots, |\mathcal{N}_n|)$$

$$G = [g_{ij}]$$

$$g_{ij} = 1 \text{ if } j \in \mathcal{N}_i$$

$$g_{ij} = 0 \text{ if } j \notin \mathcal{N}_i$$

$$Split: F(\rho) = f^{-1} (D^{-1}Gf(\rho))$$

$$(1) a = f(\rho)$$

$$(2) s = Ga \iff s_i = \sum_{k \in \mathcal{N}_i} a_k$$

$$(3) F(\rho) = f^{-1} (D^{-1}s)$$

Note that (1) and (3) can be performed element-wise, (2) only involves summation. Hence (1) and (3) are O(n). How about the "neighborhood sums" in (2)?



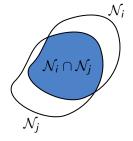
Basic idea for fast evalution of neighborhood sums

Q: Given
$$\sum_{k \in \mathcal{N}_i}$$
 how should we compute $\sum_{k \in \mathcal{N}_j}$?

- ► Compute from scratch Complexity: |N_j|
- Update using:

$$\sum_{k \in \mathcal{N}_j} = \sum_{k \in \mathcal{N}_i} + \sum_{k \in \mathcal{N}_j \setminus \mathcal{N}_i} - \sum_{k \in \mathcal{N}_i \setminus \mathcal{N}_j}$$

 $\begin{array}{l} \text{Complexity:} \ |\mathcal{N}_j \setminus \mathcal{N}_i| + |\mathcal{N}_i \setminus \mathcal{N}_j| = \\ |\mathcal{N}_j| + |\mathcal{N}_i| - 2|\mathcal{N}_i \cap \mathcal{N}_j| \end{array}$



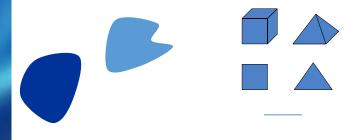
Conclusion: If the overlap is large updating is favorable. The next question is: How favorable?



The significance of neighborhood geometry

Q: Given $\sum_{k \in N_i}$, how many operations are needed to compute the sum at an *adjacent* element using the update strategy?

- Only elements on the *boundaries* of the two neighborhoods are needed (O(r^{d-1}) elements)
 - Computational complexity: $O(n^{2-1/d})$
- ▶ The facets of a polytope in \mathbb{R}^d are polytopes in \mathbb{R}^{d-1}
 - Perform updates in a recursive manner!





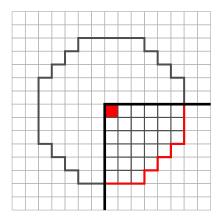
 n_v elements nd elements q۲ r2r + 1

- $\blacktriangleright n = n_1 n_2$
- ▶ $r < \min\{n_1/2, n_2/2\}$
- ▶ a_{i,j} summands
- ► s_{i,j} sums



Step 1

- ▶ Compute *s*_{1,1} from scratch
- Complexity: $< (r+1)^2$





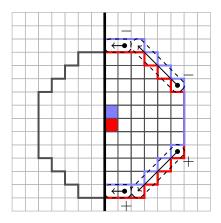
Step 1

- Compute $s_{1,1}$ from scratch
- Complexity: $< (r+1)^2$

Step 2

▶ Compute s_{i,1} by updating s_{i-1,1}

• Complexity:
$$4(n_1 - 1)$$





Step 1

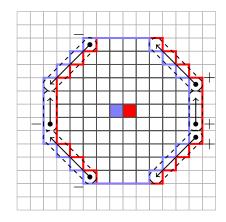
- Compute s_{1,1} from scratch
- Complexity: $< (r+1)^2$

Step 2

- ▶ Compute s_{i,1} by updating s_{i-1,1}
- ▶ Complexity: 4(n₁ − 1)

Step 3

- Compute s_{i,j} by updating s_{i,j-1}
- Complexity: $6n_1(n_2-1)$





Step 1

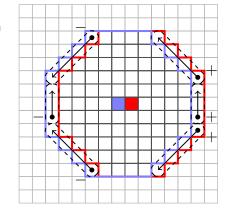
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Complexity of each 1D-sum: < 2n



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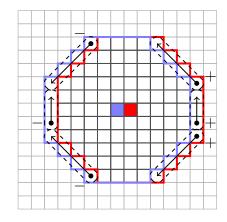
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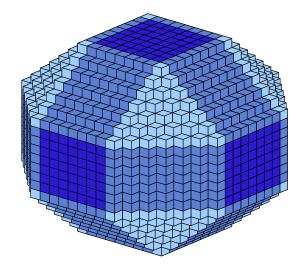
- Compute s_{i,j} by updating s_{i,j-1}
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Complexity of each 1D-sum: < 2nOverall complexity (to leading order): < 13n



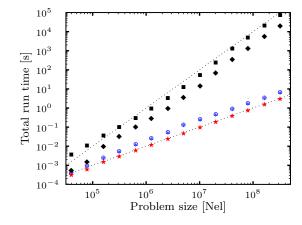
Rhombicuboctahedral neighborhoods



Overall complexity (to leading order): < 61n



Execution times for various problem sizes



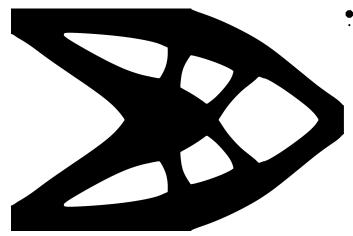
Standard $O(n^2)$ algorithm Proposed O(n) algorithm Baseline: create and write *n* random numbers to memory

L. Hägg, Megapixel Topology Optimization using fW-mean Filters, August 2015

(13:14)



Harmonic open-close megapixel optimization



- $\blacktriangleright~2160 \times 1440 \approx 3.11 \cdot 10^6$ design variables
- Four consequtive *fW*-mean filters provide independent size control on both material and void regions